Built Environment Contributing Factors to a Dominant Collision Type at Intersection Level

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Abstract

Although it is reasonable to hypothesize that it is important to understand the dynamics of different types of collision in order to promote transportation safety, much research has focused on a specific type of collision. The goal of this paper is to examine the contribution of the built environment to a specific collision type becoming a dominant type of collision at intersection level. In order to achieve this goal, this paper constructs a multi-nominal logistic regression model based on 882 intersections in the County of Los Angeles. The outputs of the models indicate the clear contribution of built environment to different types of collision. Especially, automobile collision and bicycle collision associate with built environment, which bicycle collision is less impacted by built environment. The outputs of the model suggest that these types of collisions are influenced by transportation factors, but surprisingly intersection characteristics do not limitedly associate with all three types of collision. They include roadway density, intersection density, and automobile speed. Especially, automobile speed is the only one variable that influence all three types of collision. While bicycle lane contributes to not only bicycle safety, but also automobile safety, socio-demographic variables present a statistical significance with pedestrian collision.

Introduction

Roadway safety has been a top priority transportation topic in the United States since roadway safety influences not only regional mobility, but also people's live. During the year of 2014, 32,675 fatalities and more than 2,338,000 injuries occurred on the US roads. Road accidents were the leading cause of death among ages 16 through 24 in 2014 in the U.S. (NHTSA, 2015). The fatalities and injuries become significant threats to healthy lives, which could have been saved by the application of appropriate safety countermeasure treatments.

For this reason, a large volume of research has focused on roadway safety from the identification of collision hotspots to analysis of contributing factors to collision. Since traffic collision is a phenomenon between multiple travelers, typically transportation modes that are involved in a collision, it is important to understand the dynamics between multiple transportation modes on the roadways. However, the approaches employed by much research tend to be polarized, either aggregating all types of collision or addressing an individual type of collision.

While much research on the identification of collision hotspots does not pay attention to the types of collision, it equally treats each collision as an entity that contributes to the formation of collision hotspot (Thakali et al., 2015; Huang et al., 2014; Montella, 2010). Although this method can be an objective, quantitative approach, this approach tends to be skewed by automobile collision since automobile collision most frequent type of collision. Consequently, the results from the research typically underestimates the unique characteristics of pedestrian and bicycle collisions. Some research attempted to fill this research gap by focusing on the identification of hotspots by individual collision type such as pedestrian or bicycle collision hotspot (Bejleri et al., 2007; Loukaitou-Sideris et al., 2007).

The tendency that solely studies each individual collision type becomes clearer in the research on contributing factors to collision since behavior and pattern of each transportation mode that may contribute to collision are different. Research mainly finds the causes of automobile collisions from the roadway design and characteristics. They include street layout, road networks, pavement condition, and speed (Lee and Mannering, 2002; Aarts and Schagen, 2006; Karlaftis and Golias, 2002). In addition, the behavior of drivers including alcohol consumption and cell phone handling was also identified as contributing factors to collisions between automobile and automobile (Olson and Dewar, 2007; de Carvalho Ponce et al., 2011).

The contributing factors to pedestrian and bicycle collisions are much complex. They are broken down into the behavior of travelers; the social characteristics of victim; the physical, and land use characteristics of collision location; and roadway/traffic characteristics (FHWA (A) 2017). Some research has found the influence of socio-demographic factors on collisions. These factors include low income, high youth population density, high unemployment rate, lower senior population, and more people taking public transit to work (LaScala et al., 2004; Rothman et al., 2014; Dai and Jaworski, 2016). Furthermore, a growing body of research has paid attention to the built environmental contributing factors to collisions. This includes land use factors such as population density, strip commercial and retail, big box stores, schools, and public transit

stops (Dumbaugh and Li, 2010; Wedagama et al., 2006; Dai and Jaworski, 2016; Schuurman et al., 2009). Other studies point out that pedestrian oriented design factors such as sidewalks, signalized crosswalks, marked crosswalks, roundabouts, speed humps and cushions contribute to improving pedestrian safety (FHWA (B), 2017; Schneider et al., 2004).

The research, both aggregating collision types and addressing an individual collision type, lacks of comprehensive, comparative approach that pays attention to unique characteristics of each type of collision and the interrelationship between collision types. Unless the collisions occur on highways and expressways that bans the access of pedestrians and bicycles, it is reasonable to hypothesize that automobile collision hotspots are spatially separated from pedestrian and/or bicycle collision hotspots and that the contributing factors to automobile collisions are different from to the contributing factors to pedestrian and/or bicycle collisions. These hypotheses can be tested by comparably analyzing the types of collision.

In order to test the hypotheses, this paper attempts to identify the collision hotspots of three types of collision including automobile, pedestrian, and bicycle. Using Los Angeles County as its study area, this paper especially identifies the dominant collision types at intersection since intersections are recognized as being among the most hazardous locations on the roads. This can be due to the number of different conflicting maneuvers and/or their design characteristics. Automobile is more likely to intermingle with pedestrians and bicycles, and severe crashes, such as angle crash, are likely to occur at intersections.

After the identification of dominant collision type at intersection, this paper analyzes the contributing built environment factors to the dominant collision type at intersection. In other words, this paper tests the hypothesis that built environment characteristics of intersections and surround areas significantly affect different types of collision, all else being equal. In order to achieve this research goal, this study employs a multinominal logistic (MNL) model and measures the correlations between built environment factors and the probability of a particular type of collision to become a dominant collision type in comparison to the intersections that have no dominant collision type.

Research Method

Multinomial logistic (MNL) model is used to predict a nominal dependent variable given one or more independent variables. Since the dependent variable complied is a categorical variable that represents the collision types commonly occurred at each intersection, MNL model is an appropriate analysis method for this project. This MNL approach is introduced in equations (1) through (4). Applying the MNL model requires calculation of built environment, which is proportional to the sum of four common collision types. That is,

$$\text{Prob}(y = Auto) = \frac{e^{U_{Auto}}}{e^{U_{Auto}} + e^{U_{Ped}} + e^{U_{bike}} + e^{U_{None}}},$$

$$\text{Prob}(y = Ped) = \frac{e^{U_{Ped}}}{e^{U_{Auto}} + e^{U_{Ped}} + e^{U_{bike}} + e^{U_{None}}}, \quad (1)$$

$$\text{Prob}(y = Bike) = \frac{e^{U_{Bike}}}{e^{U_{Auto}} + e^{U_{Ped}} + e^{U_{bike}} + e^{U_{None}}}, \text{ and}$$

$$\text{Prob}(y = None) = \frac{e^{U_{None}}}{e^{U_{Auto}} + e^{U_{Ped}} + e^{U_{bike}} + e^{U_{None}}},$$

where Uj is utility function of j type of collision;

j= Automobile collision (Auto), pedestrian collision, bicycle collision (Bike), and No dominant collision type (None)

$$\log\left[\frac{\text{Prob}(\text{y} = j)}{\text{Prob}(\text{y} = Auto)}\right] = \sum_i \beta_i^j X_i \quad (2)$$

Also,

where j= No dominant collision type (None), pedestrian collision, or bicycle collision (Bike), and

i = independent variables, X, affecting the collision types including built environment variables.

Equation (2) connects log transformed odds ratio for a common collision type at the intersection j in the left hand side to the product of the parameters and independent variables as a linear structure. Hence, by introducing a multinomial logit link function defined as,

$$g^j(x) = \sum_i \beta_i^j X_i = \log\left[\frac{\text{Prob}(y = j)}{\text{Prob}(y = Ped)}\right] \quad (3)$$

$$g^j(x) = \sum_i \beta_i^j X_i = \log\left[\frac{\text{Prob}(y = j)}{\text{Prob}(y = Bike)}\right] \quad (4)$$

We can substitute the utility function of Uj with multinomial logit link function gj(x) and combine the equations (1) and (2). The utility function of the collision types is estimated in equation (5).

$$U_j(x) = \sum_i \beta_i^j X_i \quad (5)$$

The predicted Uj(x) is added to calculate the probability of behavior choice in equations (1)

For the MNL model, this paper selects 882 intersections on primary and arterial roads excluding highways and expressways since pedestrian and bicycle traffic is prohibited on these roads. Because there is limited number of collisions occurred at local roads, this paper excludes the intersections on the local roads, too.

Dependent variables

The dependent variable is a categorical variable that represents a dominant type of collision at each intersection. Thus, the intersections in the study area are classified into four categories of intersections; automobile collision dominant intersections, bicycle collision dominant intersections, pedestrian collision dominant intersections, and the intersections that have no dominant type of collision. This study initiates the process of this categorization with measuring the numbers of collision that occurred at each intersection by the type of collision.

The collision was measured with the statewide integrated traffic records system (SWITRS)'s collision record data in 2012. According to the SWITRS data, there were 50,747 collisions occurred in year 2012 within the boundary of Los Angeles County. Of these collisions, any collision within the 300 feet from the intersection was defined as intersection collision. The distance of 300 feet indicates the Intersection Sight Distance (ISD). This indicates the distance that is necessary for drivers to stop control of the minor road approaches and to use their eye and object heights associated with passenger cars. On a road which has an average speed of 40 miles per hour a collision can be avoided within this 300-feet distance (AASHTO, 2004). The number of collision occurred within the 300 feet distance from the 882 selected intersections are 3,628 in total, which is equivalent to about 7.2 percent of total collisions in the county. They include 2,863, 384, and 382 automobile, pedestrian, and bicycle collisions, respectively.

After counting the number of collisions by type and by intersection, this paper normalized the collision counts by vehicle miles traveled (VMT), which was collected from th local metropolitan planning organization (MPO), Southern California Association of Governments (SCAG). The VMT applies to all types of collision including automobile, pedestrian, and bicycle. The normalized value represents the number of collisions per 1,000 VMT. It would be ideal to normalize pedestrian and bicycle collision by pedestrian and bicycle traffic volume along with VMT since pedestrian and bicycle collision is the results from the interaction of automobile with pedestrian and bicycle, respectively. However, due to the lack of pedestrian and bicycle traffic volume data in the study area, this study does not incorporate the volume data into this normalization process.

This paper identifies the dominant collision type for each intersection by employing the spatial statistic method, named, Getis-Ord Gi*. The Getis-Ord Gi* statistic identifies those clusters of geometries with values higher in magnitude than you might expect to find by random chance. The outputs of Getis-Ord Gi* analysis include a z score and a probability value for each intersection. The z score represents the statistical significance of clustering for a specified distance. The Getis-Ord Gi*model takes the following form:

$$Getis - Ord\ Gi^* = \left(\frac{\sum_{j=1}^{n} W_{ij} Z_j}{\sum_{j=1}^{n} Z_j} - \frac{\overline{Z} \sum_{j=1}^{n} W_{ij}}{n-1}\right) \Big/ \sqrt{S^2}$$

where:

Wij = 1 When feature i is adjacent to feature j, otherwise Wij = 0

Zj = Attribute value of feature j

$\overline{\mathbf{Z}}$ = The mean of attribute values

S^2 = Variance of attribute values

n = total number of features

This paper identified a collision type that commonly occurred at intersection by conducting an individual Getis-Ord Gi* analysis by each type of collision. Of the 882 intersections, 41, 32, and 23 intersections are exclusively identified as the intersections that are dominated by automobile, pedestrian, and bicycle collisions, respectively (P-value ≤ 0.1). In addition, 29 intersections were repeatedly identified as the hotsopt of two different collision types. The dominant collision types for the intersections were determined by a higher z from the Getis-Ord Gi* analyses. 756 out of 882 intersections were identified as the intersection with no dominant type of collision including one intersection presents the cluster of high collision values for all three types of collision. Through this comparison process, this paper is able to categorize 882 intersections into four categories by the type of dominant collision at each intersection (Table 1). This paper uses these categories as the dependent variable for the MNL model (Figure 1).

Table 1. The Number of Intersections by Dominant Collision Type

Dominant Collision Type	Automobile	Pedestrian	Bicycle	None	Total
Intersections	49	45	31	757	882

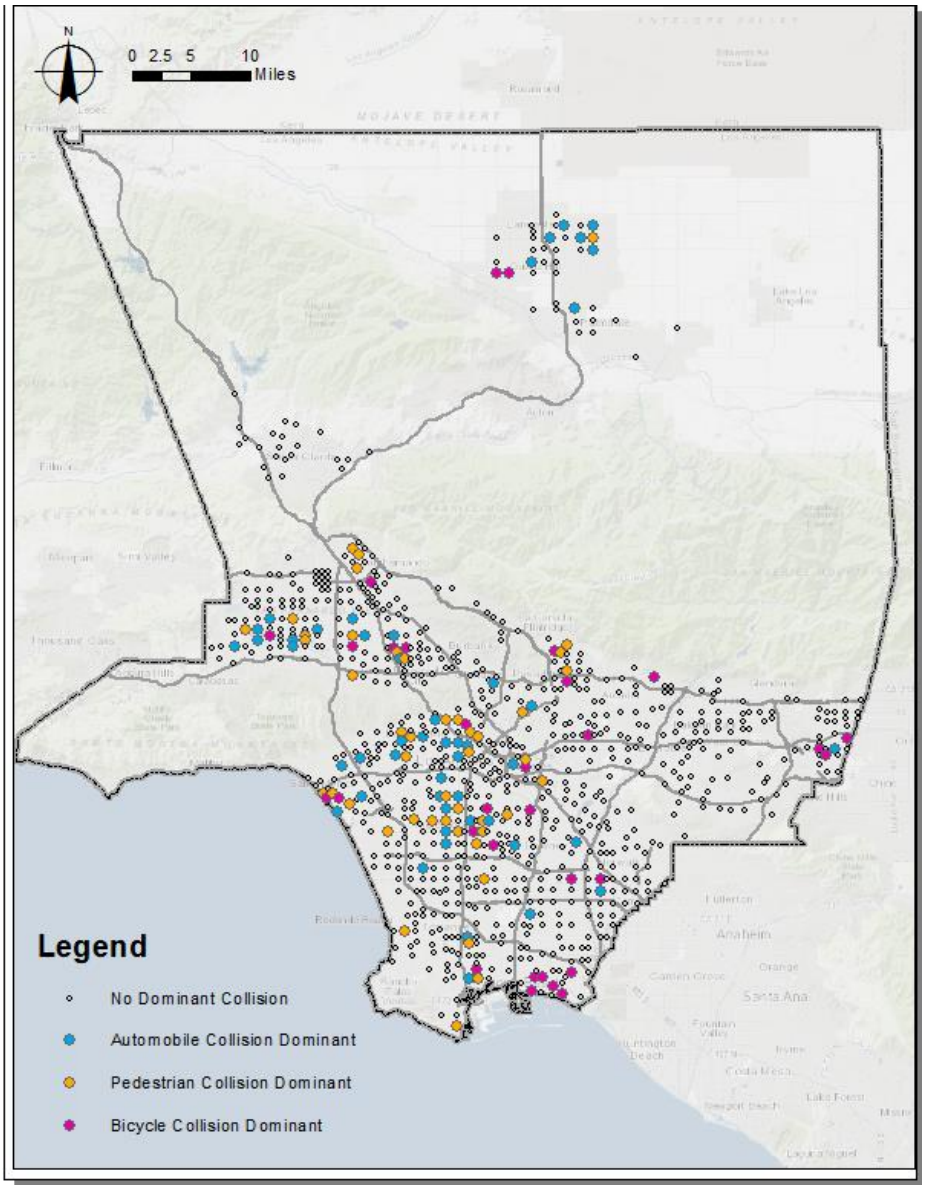

Figure 1. The Categories for the Dependent Variable

Independent variables

In order to construct the MNL model, this paper measured a variety of the built environment characteristics of the selected intersections applying a quarter mile buffer to the intersections. They are classified into the four broad categories; Intersection Characteristic, Transportation Factor, Socio-demographic Characteristic, and Land Use Factor. Each category includes a list of variables (Table 2). A series of spatial analysis was conducted to measure all the variables except one in the category of Intersection Characteristic.

Table 2. The List of Independent Variables

Name	Definition	Description
Intersection Characteristics		
Signal	Signalized intersection	Dummy (1 = all of roadways are equipped with traffic signal, otherwise 0)
CrossWlk	Missing crosswalks	Dummy (1 = at least one segment of roadway misses crosswalk, otherwise 0)
LeftTurn	Permissive left turn lane and signal	Dummy (1 = all of roadway segments have permissive left turns, otherwise 0)
RightTurn	Permissive right turn lane and signal	Dummy (1 = all of roadway segments have permissive right turns, otherwise 0)
SideWlk	Sidewalks availability	Dummy (1 = all of roadway segments have sidewalks, otherwise 0)
BikeLn	Bike lane availability	Dummy (1 = at least one roadway segment has bicycle lane, otherwise 0)
Transportation Factor		
IntsectDen	Intersection density	The number of intersections
RdDen	Roadway density	The length of roadways (in mile)
BusStop	Bus Stop density	The number of bus stops
SpdLmt	Speed limits	Proportional average speed limits of roadways
RailAcess	Rail Transit accessibility	Dummy (1 = at least one rail transit station, otherwise 0)
Socio-Demographic Characteristic		
PopDen	Population density	The number of people
EmpDen	Employment density	The number of employees
MedHHInc	Income	The median household income
MinorPop	Minority population	The number of non-White population
ComMode	Commute with non-automobile	The percent of employees who make their commuting trips with other transportation modes than automobile
Land Use Factor		
ResiUse	Residential Land Use	The acres of residential land use
ComUse	Commercial Land Use	The acres of commercial land use
OffUse	Office Land Use	The acres of office land use
Schl	K-12 School	Dummy (1 = at least one K-12 school otherwise 0)
RestFood	Restaurant Density	The number of restaurants

This paper collected the variables under the category of Intersection Characteristic through a virtual observation using Google Maps Street View. For the observation, this paper virtually visited every intersection in the Google Maps Street View, observed the characteristics of the intersection, and manually recorded the variables. A series of geo-spatial analysis is employed to measure all the variables under other categories than Intersection Characteristic. For the analysis, this study collects a variety of data from SCAG and other agencies like Los Angeles Metro and U.S. Census. The type of geometry mainly determines the suitable geo-spatial analysis for each variable. For the variables represented in the format of point like restaurant density, intersection density, bus stop and employment density, the analysis requires to count the number of points within the buffer. This study computes the variables expressed with line for each buffer by breaking the roadway line segments using intersect tool and calculating total miles of roadway for each buffer. The variables include roadway density and average speed limits. Average speed limits (SpdLmt) refers to the proportional average of speed limit within a buffer, as suggested in the following equation:

$$\sum \frac{L_j}{T} \times j$$

where Lj = Length of roads with speed limit, j
j = speed limit, and
T = total length of roads within a census tract.

It is noteworthy that there is difference between speed limit and actual traffic speed. It is ideal to measure automobile speed with actual traffic speed, but this paper employs the average speed limit variable as a proxy variable due to the lack of actual traffic speed data.
Similarly, the variables in the format of polygon including population, income, non-white population, and commute without automobile are computed employing the geographically weighted average method. This method refers to the average of variables weighted by the proportion of the area taken by each census block-group.

Results

Overall, the MNL model generated reasonably consistent results. The pseudo R-squared values from the MNL model present a moderate model fit (Table 3). As indicated in the large value of -2 log likelihood from the MNL model, the presents a strong model fit. The pseudo R square values also indicate that the outputs of the MNL model are acceptable. The closer value of Cox and Snell and Nagelkerke to 1, the stronger model fit is. The values of McFadden from 0.2 to 0.4 are considered highly satisfactory. Therefore, the MNL model presents a moderate to strong model fit.

Table 3. Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests			Pseudo R-Square		
	-2 Log Likelihood	Chi-Square	df	Sig.	Cox and Snell	Nagelkerke	McFadden
Intercept Only	990.026						
Final	741.826	248.199	66	0.00	0.245	0.364	0.251

Table 4. Descriptive Statistics of Independent variables

Variable	Minimum	Maximum	Mean	Standard Deviation
IntsectDen	2	114	33.79	15.31
RdDen	1.06	16.65	5.54	1.90
BusStop	0	475	33.33	42.02
SpdLmt	21.94	52.12	29.74	5.30
PopDen	0	86.89	15.53	10.45
EmpDen	0	2172.00	129.86	169.16
MedHHInc	0	194,225.08	52,181.91	23,051.27
MinorPop	0	1.00	0.36	0.17
ComMode	0	1.00	0.11	0.11
ResiUse	0	100.95	17.35	14.45
ComUse	0	101.50	46.31	23.52
OffUse	0	77.76	4.11	6.35
RestFood	0	2172.00	129.85	169.14

Note: The dummy variables are not included in the descriptive statistics

Table 5. The Outputs of Multinominal Logistic Regression

	Automobile Collision					Pedestrian Collision					Bicycle Collision				
	Coef.	Std.E.	Wald	Sig.	Exp(B)	Coef.	Std.E.	Wald	Sig.	Exp(B)	Coef.	Std.E.	Wald	Sig.	Exp(B)
Intercept	2.841	3.467	0.671	0.413		2.003	4.636	0.187	0.666		9.742	4.451	4.791	0.029	
Intersection Characteristic															
Signal	0.508	0.835	0.371	0.543	1.662	-0.391	0.748	0.273	0.601	0.676	0.695	0.819	0.720	0.396	2.003
CrossWlk	0.775	0.735	1.112	0.292	2.171	-0.228	0.624	0.134	0.715	0.796	0.307	0.738	0.173	0.677	1.360
LeftTurn	-0.649	0.380	2.913	*0.088	0.522	-0.398	0.391	1.038	0.308	0.671	-0.344	0.480	0.515	0.473	0.709
RightTurn	1.252	1.063	1.387	0.239	3.498	3.618	3.220	1.262	0.261	37.268	0.774	1.072	0.522	0.470	2.169
SideWlk	0.566	0.852	0.440	0.507	1.760	0.934	0.738	1.598	0.206	2.543	0.677	0.763	0.789	0.375	1.968
BikeLn	-0.897	0.350	6.585	**0.010	0.408	-0.320	0.369	0.750	0.386	0.726	-0.740	0.429	2.968	*0.085	0.477
Transportation Factor															
IntsectDen	0.036	0.020	3.098	*0.078	1.036	0.052	0.020	6.755	***0.009	1.054	0.019	0.020	0.894	0.344	1.020
RdDen	-0.407	0.214	3.619	*0.057	0.666	-0.492	0.212	5.379	**0.020	0.612	-0.034	0.214	0.026	0.873	0.966
BusStop	-0.009	0.006	2.198	0.138	0.991	0.013	0.006	5.184	**0.023	1.013	0.001	0.006	0.014	0.905	1.001
SpdLmt	0.240	0.095	6.353	**0.012	0.787	0.246	0.098	6.311	**0.012	0.782	0.423	0.131	10.464	***0.001	0.655
RailAcess	-0.523	0.629	0.691	0.406	0.593	-0.221	0.626	0.125	0.723	0.801	-1.074	0.686	2.450	0.117	0.342
Socio-Demographic Characteristic															
PopDen	0.062	0.020	9.493	***0.002	1.064	0.028	0.021	1.709	0.191	1.028	0.047	0.027	2.973	*0.085	1.048
EmpDen	-0.098	0.400	0.061	0.806	0.906	-0.689	0.001	22K.49	***0.000	0.502	-1.766	0.001	155K.96	***0.000	0.171
MedHHInc	0.000	0.000	2.617	0.106	1.000	0.000	0.000	3.128	*0.077	1.000	0.000	0.000	3.364	*0.067	1.000
MinorPop	-1.271	1.074	1.400	0.237	0.281	-2.541	1.138	4.987	**0.026	0.079	-2.104	1.387	2.301	0.129	0.122
ComMode	-1.307	2.576	0.258	0.612	0.271	2.598	2.174	1.428	0.232	13.441	-5.848	3.811	2.354	0.125	0.003
Land Use Factor															
ResiUse	0.025	0.019	1.753	0.185	1.025	0.069	0.020	12.000	***0.001	1.072	0.017	0.023	0.518	0.472	1.017
ComUse	0.003	0.013	0.052	0.820	1.003	0.042	0.015	8.158	***0.004	1.043	0.001	0.015	0.007	0.936	1.001
OffUse	-0.048	0.045	1.153	0.283	0.953	-0.067	0.046	2.186	0.139	0.935	-0.003	0.046	0.006	0.940	0.997
Schl	-0.761	0.342	4.962	**0.026	0.467	-0.268	0.349	0.588	0.443	0.765	0.450	0.419	1.151	0.283	1.568
RestFood	0.100	0.400	0.062	0.803	1.105	0.687	0.000			1.988	1.766	0.000			5.849

Note: *, **, *** Correlations are significant at the 0.10, 0.05, and 0.01 levels, respectively (2-tailed)

The reference category is the intersections that do not have a dominant collision type.

Overall, the outputs suggest that built environmental factors mostly influence the probability of pedestrian collision to be common at intersection in comparison to automobile and bicycle collisions. Of the twenty-one built environment variables, pedestrian collision presents statistically significant associations with ten variables, while automobile and bicycle collisions show the association with seven and five variables, respectively (Table 5).

Discussion

It is surprising to find out that the impact of intersection characteristics on collision is minimal. Of six intersection characteristic variables, two variables, LeftTurn and BikeLn, negatively associate with automobile collision, while BikeLn also negatively associates with bicycle collision. None of intersection characteristics correlates with pedestrian collision at a statistically significant level. Much research identifies collision as the dynamic between traffic at a micro level like intersection. Thus, the contribution of infrastructure and/or feature at intersection to collision is considered highly important. However, the outputs of the MNL model suggest that other factors than intersection characteristics, especially transportation factor that represents transportation infrastructure and condition in adjacent areas, make a particular type of collision dominant at intersection.

The outputs present interesting variations in terms of the correlations of the built environment factors with the dominant types of collision. Transportation factor is the most influential factor on automobile collision. Pedestrian collision becomes a dominant type of collision due to both transportation and socio-demographic factors. Bicycle collision mostly associates with socio-demographic characteristics. Assuming that pedestrian and bicyclists tend to get involved in collision nearby where they live, work, and/or manage their everyday life, the influence of socio-demographic factors is understandable. However, it requires further analysis on the conflicting correlation directions of the factors with pedestrian collision to one indicated in previous research. This may be caused by the fact that this paper does not normalize the pedestrian collision by pedestrian traffic. Due to the lack of pedestrian volume data, this study normalized the pedestrian collision only by automobile traffic. Thus, it is possible for the correlations to represent the relationship between pedestrian traffic volume and pedestrian collision.

Of twenty-one variables, only one variable, automobile speed (SpdLmt), presents a statistically significant correlation with all the types of collision. This implies that the intersections that each of automobile, pedestrian, and bicycle collision becomes a dominant type of collision at the intersections where automobile drives faster. The outputs indicate that automobile speed significantly influences collision regardless the type of collision. Thus, it is important to control automobile speed in order to improve overall roadway safety. In this vein, it can be expected that the current transportation policies such as traffic calming, complete streets, and road diet must positively contribute to not only pedestrian and bicycle safety, but also the safety between automobiles.

Another interesting finding is the impact of bicycle lane on traffic safety an intersection. The outputs of the MNL model suggest that bike lane positively contributes to not only bicycle collision but also automobile collision. In other words, the probability of bicycle and automobile collision to become a dominant collision type is significantly lower at the intersections that have bicycle lanes implemented. Although it is not surprising to find the contribution of bicycle lane to bicycle safety, its positive contribution to automobile safety is unexpected. This contribution is probably caused by drivers' cautious behavior. The existence of bicycle lanes as well as bicyclists on bicycle lanes probably make automobile slow down and drivers be cautious in traffic patterns and ambient environment. Therefore, the collisions not only between automobile and bicycle but also between automobile do not stand out at the intersections with bicycle lane.

A similar interpretation can apply to the relationship between automobile collision and school. The MNL model presents a negative correlation between automobile collision and the intersection that has school within quarter miles. This implies that the probability of automobile collision to become a dominant collision type significantly decreases at the intersection with school nearby. In the areas close to school, drivers probably drive more cautiously. School zone signs and signals draw drivers' attention. Especially during school entry and exit times, school zone speed enforces automobile drive slowly. Drivers pay more attention to traffic on the streets. Thus, automobile collision becomes a dominant collision type at the intersections that not close to school rather than nearby school.

Finally, the outputs of the MNL model indicate an interesting relationship between roadway safety and intersection density. Intersection density presents positive correlations with both automobile collision and pedestrian collision. This implies that intersection density contributes both types of automobile and pedestrian collision to become a dominant collision type at intersection. Intersections tend to make automobiles stop, idle, and speed up. These behaviors of automobile probably contribute to make automobile movement complex. In the areas with high intersection density, automobile should repeat the complex movements and behaviors. The model outputs represent the impact of the behaviors on automobile collision. On the other hand, the number of intersections is one of the popular indicators for walkability. The higher number of intersections indicates walkable environment, and presumably attracts pedestrians. The positive correlation between intersection density and pedestrian collision probably reflects the dynamic between large volume of pedestrian and complex movements of automobile.

Conclusions

As large volume of research has suggested, it is clear that built environment influences traffic collision, generally transportation safety. In addition to support the points of the research, this paper confirms the significance of built environment's influence on collision types. The built environmental characteristics around intersection contributes to cause a specific type of collision much more frequently than any other types. The intersections that associates with a particular

type of collision are spatially distinctive. Furthermore, the intersections have unique characteristics that probably contribute to be the type of collision dominant at the intersections.

Based on these findings, transportation planning agencies and local governments can customize their transportation safety strategies that target not only an individual collision type, but also the dynamics between different collision types. As the example of bicycle lane suggests, bicycle lane, which is typically considered as facility that promotes the safety of bicyclists, can also be an efficient option to reduce the collision between automobile. Therefore, the findings from this paper helps to develop a comprehensive, inclusive transportation safety plan.

This paper that pursues a micro-level analysis can be synchronized well with the current trend of long range transportation plan. With the advance of activity-based model, metropolitan planning organization (MPO) lately investigate and analyzes residents' travel behavior at micro geographical level such as parcel. Therefore, it is important to understand roadway safety along the travel routes that residents actually choose rather than conventional geographical boundaries like census tract or travel analysis zone (TAZ). In this vein, this paper presents a systemic analysis approach on transportation safety analysis at intersection level.

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